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A Covering Algorithm Based on Competition

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Abstract

In covering algorithm, the order of learning samples is random, but experiments show that the learning sequence has significant impact on the network performance. This paper proposes a new algorithm which is covering algorithm based on competition (CAC). In this algorithm, sphere neighborhoods can be adjusted gradually, the ill-suited sphere neighborhoods will be removed and the whole neural network will performs more stable. Finally the algorithm is applied to a widely used database. The experiment results show that it can effectively decrease the number of rejected samples, reduce the number of sphere domains and improve the recognition accuracy.

Keywords: neural network, covering algorithm, learning sequence

1. Introduction

Many years ago artificial neural networks (ANNs) were firstly developed (McCulloch and Pitts, 1943) as a simplified model of the neural tissue which made up animal neural systems [1]. Apart from this biological metaphor an ANN may be considered as a modeling function made up of sub-modeling functions, called neurons, and in this sense it may be considered as a parallel distributed processing (PDP) model. As such they are capable to generalize a phenomenon starting from experimental input–output pair of data (supervised learning) [2]. In the last fifty years ANNs have been applied in various fields, including pattern recognition, identification, classification, speech, vision and control systems. Recently, ANNs have been largely applied to specify flexible functions for classification or regression analysis and have been applied to travel demand analysis nowadays [6] with fairly satisfactory results [3]. Unfortunately, almost all training algorithms for neural networks suffer from problems of iterative

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computing and long training time. For example, Error Back-Propagation (EBP) is a popular training algorithm, but it is based on gradient descending technique and needs an extremely high number of iterations for training [5].

In 1990s, the covering algorithm for forwarding neural network was put forward, this algorithm is a constructive machine learning method and a network with sphere neighborhoods is designed to build upon sample data. The theoretical analysis indicates that the general ability of this algorithm is in the inverse ratio of the number of covering domains [4], and the number of covering domains is related with the order of study closely. Some techniques are performed while constructing the sphere neighborhood set to simplify the network, such as changing the sphere neighborhoods center to the barycentre of points covered by a domain, deleting the points covered by a sphere neighborhood [4]. In this paper, a covering algorithm based on competition (CAC) is presented.

2. Review of covering algorithm

In order to reduce the learning complexity of a neural network and still maintain the simplicity of the M-P model and its corresponding network, a new theory is presented by Zhang ling *et.al*. The key points of the theory are described as follows. The covering algorithm for neural network is based on geometrical expansion in the input hyperspace. The original input space is transferred into a quadratic space, and the well-known (point set) covering method can be applied to perform partition of data in the transform space. At the same time, the simplicity of the M-P model and its corresponding network still holds true. There is no need either to increase the complexity of node functions or the complexity of networks' structure. A simple neuron network by covering algorithm will be given as follows:

Given a set $Y=\{(X^1,y^1),(X^2,y^2)...(X^l,y^l)\}$ （l=0,1,2…. X is vectors in n-dimensional sphere） of training samples. Assume that outputs of samples can be classified into S classes. Let I(t) be a set of indices of samples with the same output, $\mathrm{I}(t)=\{i \mid y^i=y^t\}$, the input set corresponding to *I(t)* can be expressed as $p(t)=\{x^i \mid i\in I(t)\}$,t=0,1,2…S-1.

A set $\{C_m^k, m=1,2...\}$ of sphere neighborhoods (coverings) is chosen as $C(k)=\bigcup C_m^k$ covers every input $x^i\in p(k)$ and does not cover any inputs $x^i\notin p(k)$.

One possible covering approach is as follows

$$d1(j)=\min_{x^m\notin Y_k}\{d(x^j,x^m)\}$$

$$d2(j)=\max_{x^m\in Y_k}\{d(x^j,x^m)<d1(j)\}$$

$$d(j)=[d1(j)+d2(j)]/2$$

$$\theta(j)=[d1(j)-d2(j)]/2$$

$d1(j)$ is the minimum "distance" between x^m and $x^j\notin p(t)$

$d2(j)$ is the maximum "distance" between x^m and x^j belong to p(t) and at a distance less than $d2(j)$ from x^m.

$$C_m^k=\{x \mid (x,x^m)<d(j)\} \tag{1}$$

$$C(k)=\bigcup_{m\in I(k)} C_m^k \quad \mathrm{K}=0,1,2\ldots\mathrm{K}-1. \ , \tag{2}$$

The neuron corresponds to a covering C_m^k, a neighborhood on S^n sphere with x_m as its center and $d(j)$ as its radius. The coverings $m2 \in p(k)$ are the neurons in the first layer of a neural classifier and the inputs are classified into different classes by the first layer [7] [8].

3. View of CAC

Covering algorithm has some advantages, but the learning order of the algorithm is randomly selected. Experiments show that the learning sequence has a significant impact on the network performance. In covering algorithm if a covering center is chosen, the center will be considered right and the points which are covered by the center must be deleted from samples. Because the covering center is chosen randomly, it is not always appropriate. Thus the performance of network is not steady. In this paper a covering algorithm based on competition (CAC) is proposed. In CAC, when a covering center is chosen, the points which are covered by it are not removed so the following centers can also cover it and the points will mark the covered times. The next covering center will be chosen from those points which are covered for most times. If a covering center is covered by others, it will be deleted from covering center set. A neuron network can be described as the following steps.

Use the samples data in section 2.

Step1: Get a sphere neighborhood C_{m1}^k with center $m1 \in p(k)$ and sphere neighborhood C_{m2}^k with center $m2 \in p(k)$ by normal covering algorithm. The points $x^i \in p(k)$ mark the covered times.

Step2: Choose a point 'A' for center from points which are covered mostly.

Step3: Get a sphere neighborhood C with A which is its center.

Step4: Compare C with other covering centers which cover the same class samples.

Step4.1: If C is covered by any other covering centers, C is not appropriate and goes back to step 2 or keep C into covering set. If any covering center is covered by C and then the covering center is deleted.

Step4.2: the points which are covered by C mark their covered times plus.

Step5: If all the points $x^i \in p(k)$ are covered yet, go to step6, or go back to step 2.

Step6: $C(k) = \bigcup C_m^k$

4. Experiments and analysis

To illustrate the advantage of CAC, we test our algorithm on a widely used dataset, Iris dataset [9], for classification, and compare it with normal covering algorithm. The Iris dataset consists of three target classes: Iris Setosa, Iris Virginica and Iris Versicolor. Each species contains 50 data samples. Each sample has four real-valued features: sepal length, sepal width, petal length and petal width. In the neuron network, three types of output neurons are required to represent samples classes.

We use half of the data samples for training and the remained for testing. The results of CAC classification for the training set and testing set are reported in second row in Table 1, and the results of normal covering algorithm classification are in third row in Table 1.

As is shown in Table 1, CAC is better than normal covering algorithm in both testing accuracy and the number of neurons, and the performance of network trained by CAC is more stable. Generally speaking, the impact of the order of samples' learning is weakened by CAC and the sphere neighborhood is more appropriate, so the neural network trained by CAC is better than that trained by covering algorithm.

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Table 1 The results of CAC classification for the training set and testing set

Method	number of training data	number of testing data	number of neurons	Misclassified for testing set	Accuracy for testing set (%)
CAC	75	75	11.5	3	96
Normal covering algorithm	75	75	15	7	90.67

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